Open Access
J. Glob. Innov. Agric. Sci., 2023, 11(3):319-332
ISSN (Online): 2788-4546; ISSN (Print):2788-4538
DOI: https://doi.org/10.22194/JGIAS/11.1110
http://www.jgiass.com

Impact of climate change on agricultural production in Burkina Faso, West Africa

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Global warming is one of the greatest challenges of this century. It impacts all nations worldwide, particularly Sahelian nations in Africa. This article evaluates climate change's impact on aggregate agriculture, crop, livestock, and fishery production in Burkina Faso. The autoregressive distributed lag (ARDL) model was applied, and data were collected from 1990 to 2019. Considering agriculture at the aggregate level, the findings have shown an insignificant effect of rainfall and temperature but a positive impact of carbon dioxide (CO_2) in the long run. Only rainfall negatively affects agriculture in Burkina Faso in the short run. For crop production, only CO_2 is found to have a short-run negative effect. The findings indicated that temperature has a short-term favorable effect on livestock production, whereas CO_2 benefits it in the long term. The long-run time series analysis of fishery production has indicated a detrimental impact of rainfall. In the short term, temperature, rainfall, and CO_2 have a detrimental impact on fishery production in Burkina Faso. However, CO_2 is found to have a short-run negative impact. Promoting and facilitating livestock production and irrigation systems and enhancing climate system information (CSI) could lessen agriculture's sensitivity to global warming.

Keywords: Agriculture and sub-sectors, climate change, ARDL, Burkina Faso, west africa.

INTRODUCTION

The issue of global warming is one of the most pressing in our time, as it affects every nation and has a devastating effect on people's living standards everywhere (Erenstein and Ali, 2017; Xie *et al.*, 2018). Greenhouse gases have been released into the atmosphere due to human activities, especially industrial ones (Shi *et al.*, 2018). As a result, the planet warms, and weather extremes like droughts and floods become more common.

Africa endures most of the consequences of climate change, despite contributing only 10% to global pollution levels (IPCC, 2014; Sarker *et al.*, 2014). Sub-Saharan Africa (SSA) is predicted to be hit particularly hard by the effects of climate change (CC) (Bakshi *et al.*, 2019; Bornemann *et al.*, 2019; Lokonon *et al.*, 2019; Baarsch *et al.*, 2020). In Sub-Saharan Africa, the Sahel and West Africa appear especially vulnerable to global warming (Baarsch *et al.*, 2020). According to Zhang *et al.* (2019), the Sahel region is vulnerable to unfavorable weather and has a very low adaptive capacity. Because of its significant reliance on rain-fed agriculture and its weak economic and institutional capacity to adjust to climatic variability and change, West Africa is known to be particularly vulnerable to climate change (Sultan and Gaetani, 2016). As a result, the Sahel region of West Africa is anticipated to bear the greatest impact of climate change.

Given its reliance on rain-fed agriculture, Zidouemba (2017) warns that the economic development of Burkina Faso, a West African and Sahelian country may be particularly sensitive to the effects of climate change. In fact, Busby *et al.* (2014) identify Burkina Faso as one of Africa's most at-risk nations due to climate change. Burkina Faso is a landlocked country in the Sahelian region of West Africa, with a low Human Development Index (HDI, ranked 182 out of 189 countries) (UNDP, 2019) and several types of malnutrition issues (FAO *et al.*, 2018; USAID, 2018). Similarly, poverty is prevalent, with 43.7% of Burkina Faso's population having a daily income of less than $1.9 USD (World Bank, 2019). Considering its low position (138th out of 157) in meeting the Sustainable Development Goals (SDGs) so far (Schmidt-Traub *et al.*, 2017; USAID, 2018), the country must also close its gap in sustainable development. The agriculture sector is a major economic driver, responsible for 28.3% of jobs and 28.6% of GDP (World Bank, 2019). Cowpea, sorghum, millet, maize, and rice are grown for subsistence, while cotton

Dossa, L.I.KE-T., M.K. Bashir, S. Hassan and K. Mushtaq. 2023. Impact of climate change on agricultural production in Burkina Faso, West Africa. Journal of Global Innovations in Agricultural Sciences 11:319-332
[Received 2 Jul 2023; Accepted 5 Aug 2023; Published 30 Sep 2023]

and groundnuts are the primary cash crops (USAID, 2017). However, due to its huge extent and dependence on summer rainfall (June–September), agriculture is very susceptible to CC. In fact, the local climate is characterized by highly variable rainfall (USAID, 2017).

Most of the studies about sub-Saharan Africa (SSA) have been done at either the regional or international level (Rosenzweig and Parry, 1994; Darwin *et al.*, 1995; IFPRI, 2009). There is not much information about the damage that could be done in each country. However, more research needs to be done at the national level on these impacts in West Africa. Different countries will experience different impacts from climate change due to differences in agricultural technologies, environmental and socioeconomic conditions. This highlights the importance of acting on a national scale to address the issue of agriculture's vulnerability to climate change.

The literature on climate change's effects on agricultural productivity varies greatly due to differences in country, agriculture sub-sector considered, and assessment techniques. Temperature impact can be negative on agriculture output (Chandio *et al.*, 2020c; Chandio *et al.*, 2022a), crop production and yield (Chandio *et al.*, 2020a, b; Pickson *et al.*, 2020; Chandio *et al.*, 2021a, b; Jan *et al.*, 2021; Warsame *et al.*, 2021; Gul *et al.*, 2022a, b), livestock production (Warsame *et al.*, 2022), and fish production (Begum *et al.*, 2022). Some studies (Chandio *et al.*, 2020a; Chandio *et al.*, 2021a, b; Emenekwe *et al.*, 2022a; Pickson *et al.*, 2022) also reported that temperature increase could benefit crop production. Temperature impact can also be insignificant on crop production, as shown in works by Janjua *et al.* (2014), Abbas (2020), and Pickson *et al.* (2022).

Some studies claimed that rainfall benefits agricultural output (Chandio *et al.*, 2022b), crop production, and yield (Chandio *et al.*, 2020a, b; Pickson *et al.*, 2020; Chandio *et al.*, 2021a, b; Jan *et al.*, 2021; Warsame *et al.*, 2021; Chandio *et al.*, 2022a, b; Ntiamoah *et al.*, 2022; Pickson *et al.*, 2022), livestock (Warsame *et al.*, 2022), and fish production (Begum *et al.*, 2022). However, this positive impact can sometimes be negative in the short term (Chandio *et al.*, 2021b; Jan *et al.*, 2021; Warsame *et al.*, 2021). Rainfall also negatively affects agricultural output (Chandio *et al.*, 2020c) and crop production (Emenekwe *et al.*, 2022a). Its impact can also be insignificant on crops (Janjua *et al.*, 2014; Gul *et al.*, 2022b; Pickson *et al.*, 2022).

CO_2 can favor agriculture (Chandio *et al.*, 2020c; Rehman *et al.*, 2020) and crop production (Ahsan *et al.*, 2020; Chandio *et al.*, 2020a; Chandio *et al.*, 2022b; Gul *et al.*, 2022b; Ntiamoah *et al.*, 2022; Pickson *et al.*, 2022). It also benefits the livestock sub-sector in the short run (Warsame *et al.*, 2022). Some research suggests that CO_2's long-term beneficial effect can be harmful in the short term (Ahsan *et al.*, 2020; Chandio *et al.*, 2022b; Gul *et al.*, 2022b). Further research indicates that CO_2 has a detrimental effect in both runs on agricultural output (Chandio *et al.*, 2022a), crop (Chandio *et al.*, 2020b; Pickson *et al.*, 2020; Chandio *et al.*, 2021a, b; Chandio *et al.*, 2022b), and fish production in the short term (Begum *et al.*, 2022). In numerous studies, it has an insignificant effect on the crop sub-sector in both runs (Janjua *et al.*, 2014; Warsame *et al.*, 2021; Ntiamoah *et al.*, 2022). Likewise, its impact can be insignificant in the long term on fish and livestock production (Begum *et al.*, 2022; Warsame *et al.*, 2022).

Few empirical studies have examined global warming's effects on Burkina Faso's agriculture (Diarra *et al.*, 2017; Nana, 2019; Sossou *et al.*, 2019). Those papers only focused on cotton production, cereal yield, and cereal production. Consequently, this paper aims to assess global warming's effects on agricultural production in Burkina Faso from 1990 to 2019. To the best of our knowledge, this is the first research to assess climate change's impact on agriculture and its many sub-sectors including crops, livestock, fishery, and forestry. Furthermore, this study is the first to employ the Autoregressive Distributed Lag (ARDL) method to evaluate how climate change may impact aggregate agriculture, crops, livestock, and fishery production in Burkina Faso.

The next section includes a presentation of the materials and methods, then the findings, discussion, and conclusion.

MATERIALS AND METHODS

***Data and variables*:** This research relied on time series collected annually from 1990 to 2019. The data used in this research comes from a wide range of national and international sources. The Climate Change Knowledge Portal (CCKP) provides information on temperature (TEMP) and rainfall (RF). The World Development Indicators (WDI) website is the data source for CO_2, agricultural GDP (AGDP), gross capital formation (GCF), and domestic credit (DC). Furthermore, we have computed values on crop GDP (CGDP), livestock GDP (LGDP), and fishery and forestry GDP (FGDP) using AGDP values in constant 2015 US dollars from the WDI, as well as the contribution of the agricultural subsectors to agriculture data from the website of the Institute of the National Institute of Statistics and Demography of Burkina Faso. This research used AGDP, CGDP, LGDP, and FGDP as dependent variables for each model to account for agriculture, crop, livestock, and fishery production, respectively. However, CO_2 emissions, average temperature, rainfall, domestic credit, and gross capital formation were employed as independent variables. Table 1 shows the description of the data, sources, and summary of descriptive statistics.

***Model*:** The present study employs the ARDL technique developed by Pesaran *et al.* (2001) to evaluate the long- and short-run effects of climate conditions on aggregate agriculture, crop, livestock, and fishery production in Burkina Faso using EViews 12 software. The ARDL method is

preferred in this empirical investigation due to its widespread adoption in the scientific literature for the analysis of cointegration and short- and long-run relationships (Abbas, 2020; Asumadu-Sarkodie and Owusu, 2016; Chandio *et al.*, 2020a, b; Warsame *et al.*, 2021). This approach possesses numerous advantages in comparison to conventional statistical methodologies. To begin, even when some endogenous factors function as regressors, the ARDL approach yields an objective long-run estimate (Adom *et al.*, 2012). Second, short-run and long-run coefficients are calculated simultaneously. Third, ARDL can be used whether the regressors are all I (0), I (1), or both. In addition, the ARDL is robust against endogeneity among variables because it is not affected by residual correlation (Pesaran *et al.*, 2001). Finally, although other cointegration approaches are sensitive to sample size, the ARDL approach gives robust and consistent findings for small sample sizes (Pesaran and Shin, 1998; Pesaran *et al.*, 2001; Adom *et al.*, 2012). The assumption of a linear relationship among independent and dependent variables is one of the model's flaws. Warsame *et al.* (2021), Abbas *et al.* (2022), Asfew and Bedemo (2022), Begum *et al.* (2022), and Emenekwe *et al.* (2022b) all agree that the method is not suited to large sample sizes.

The following linear functions were employed to express the relationship between dependent variables and climatic factors used in the study, relying on the work of Chandio *et al.* (2020c) and Pickson *et al.* (2022).

- **Model A: Effect of climatic factors on agriculture production**
  $$\mathrm{AGDP_t} = \omega_0 + \omega_1 \mathrm{TEMP_t} + \omega_2 \mathrm{RF_t} + \omega_3 \mathrm{CO_{2t}} + \omega_4 \mathrm{DC_t} + \omega_5 \mathrm{GCF_t} + \varepsilon_t \quad (1)$$
- **Model B: Impact of climate variables on crop production**
  $$\mathrm{CGDP_t} = \omega_0 + \omega_1 \mathrm{TEMP_t} + \omega_2 \mathrm{RF_t} + \omega_3 \mathrm{CO_{2t}} + \omega_4 \mathrm{DC_t} + \omega_5 \mathrm{GCF_t} + \varepsilon_t \quad (2)$$
- **Model C: Influence of climate indicators on livestock production**
  $$\mathrm{LGDP_t} = \omega_0 + \omega_1 \mathrm{TEMP_t} + \omega_2 \mathrm{RF_t} + \omega_3 \mathrm{CO_{2t}} + \omega_4 \mathrm{DC_t} + \omega_5 \mathrm{GCF_t} + \varepsilon_t \quad (3)$$
- **Model D: Impact of climate factors on fishery production**
  $$\mathrm{FGDP_t} = \omega_0 + \omega_1 \mathrm{TEMP_t} + \omega_2 \mathrm{RF_t} + \omega_3 \mathrm{CO_{2t}} + \omega_4 \mathrm{DC_t} + \omega_5 \mathrm{GCF_t} + \varepsilon_t \quad (4)$$

Where ε_t is the disturbance term in time, AGDP represents agricultural GDP, CGDP denotes crop GDP, LGDP shows livestock GDP, FGDP stands for fish and forestry GDP, TEMP indicates temperature, RF presents rainfall, CO_2 specifies carbon dioxide emissions, DC is domestic credit, and GCF stands for gross capital formation.

Estimation: The ARDL model involves two crucial phases for evaluating relationships. The first step is to check whether the variables are connected over the long run. This research used the bound test to examine the long-term correlations between dependent and independent variables across all models. According to Pesaran *et al.* (2001), there are two distinct critical values for the bound test: upper and lower bounds. Lower-bound critical values apply to I (0) types of variables. Upper-bound critical values are the critical values for I (1) variables. If the calculated F-statistic is greater than the upper boundaries, then the null hypothesis of no cointegration is rejected and the existence of long-run cointegration is supported. We must accept the null hypothesis of cointegration if the estimated F-statistic is less than the lower bound, showing no long-run relationship. The cointegration test is inconclusive if the results are within the critical values (Attiaoui and Boufateh, 2019; Demirhan, 2020; Begum *et al.*, 2022).

The variables' short- and long-term connections are explored by employing the following error correction model (ECM) representations.

- **Model A: Impact of climatic indicators on agricultural production**
  $$\Delta\mathrm{lnAGDP_t} = \omega_0 + \sum_{i=1}^{p} \theta_{1i}\,\Delta\mathrm{lnAGDP_{t-i}} + \sum_{i=0}^{q_1} \theta_{2i}\,\Delta\mathrm{lnTEMP_{t-i}} + \sum_{i=0}^{q_2} \theta_{3i}\,\Delta\mathrm{lnRF_{t-i}} + \sum_{i=0}^{q_3} \theta_{4i}\,\Delta\mathrm{lnCO_{2t-i}} + \sum_{i=0}^{q_4} \theta_{5i}\,\Delta\mathrm{lnDC_{t-i}} + \sum_{i=0}^{q_5} \theta_{6i}\,\Delta\mathrm{lnGCF_{t-i}} + \varphi \mathrm{ECM_{t-1}} + \varepsilon_t \quad (9)$$
- **Model B: Effect of climatic factors on crop production**
  $$\Delta\mathrm{lnCGDP_t} = \omega_0 + \sum_{i=1}^{p} \theta_{1i}\,\Delta\mathrm{lnCGDP_{t-i}} + \sum_{i=0}^{q_1} \theta_{2i}\,\Delta\mathrm{lnTEMP_{t-i}} + \sum_{i=0}^{q_2} \theta_{3i}\,\Delta\mathrm{lnRF_{t-i}} + \sum_{i=0}^{q_3} \theta_{4i}\,\Delta\mathrm{lnCO_{2t-i}} + \sum_{i=0}^{q_4} \theta_{5i}\,\Delta\mathrm{lnDC_{t-i}} + \sum_{i=0}^{q_5} \theta_{6i}\,\Delta\mathrm{lnGCF_{t-i}} + \varphi \mathrm{ECM_{t-1}} + \varepsilon_t \quad (10)$$
- **Model C: Influence of climate variables on livestock production**
  $$\Delta\mathrm{lnLGDP_t} = \omega_0 + \sum_{i=1}^{p} \theta_{1i}\,\Delta\mathrm{lnLGDP_{t-i}} + \sum_{i=0}^{q_1} \theta_{2i}\,\Delta\mathrm{lnTEMP_{t-i}} + \sum_{i=0}^{q_2} \theta_{3i}\,\Delta\mathrm{lnRF_{t-i}} + \sum_{i=0}^{q_3} \theta_{4i}\,\Delta\mathrm{lnCO_{2t-i}} + \sum_{i=0}^{q_4} \theta_{5i}\,\Delta\mathrm{lnDC_{t-i}} + \sum_{i=0}^{q_5} \theta_{6i}\,\Delta\mathrm{lnGCF_{t-i}} + \varphi \mathrm{ECM_{t-1}} + \varepsilon_t \quad (11)$$
- **Model D: Impact of climatic factors on fishery production**
  $$\Delta\mathrm{lnFGDP_t} = \omega_0 + \sum_{i=1}^{p} \theta_{1i}\,\Delta\mathrm{lnFGDP_{t-i}} + \sum_{i=0}^{q_1} \theta_{2i}\,\Delta\mathrm{lnTEMP_{t-i}} + \sum_{i=0}^{q_2} \theta_{3i}\,\Delta\mathrm{lnRF_{t-i}} + \sum_{i=0}^{q_3} \theta_{4i}\,\Delta\mathrm{lnCO_{2t-i}} + \sum_{i=0}^{q_4} \theta_{5i}\,\Delta\mathrm{lnDC_{t-i}} + \sum_{i=0}^{q_5} \theta_{6i}\,\Delta\mathrm{lnGCF_{t-i}} + \varphi \mathrm{ECM_{t-1}} + \varepsilon_t \quad (12)$$

Here, ECM connotes the error correction model, and φ shows its coefficient, representing the adjustment time required to return to equilibrium after a short-term shock to the system. For a significant ECM model, φ should be negative (Janjua *et al.*, 2014). By taking the coefficient of φ to be significantly negative, empirical research shows that any temporary shock in the short term will automatically converge to equilibrium in the long term (Omoke *et al.*, 2020; Emenekwe *et al.*, 2022b).

RESULTS

In this analysis, only FGDP, CO_2, DC, and GCF have been transformed into their logarithmic forms. The other variables have been used as such. However, graphical analysis and descriptive statistics have been done on the raw data to capture the natural characteristics of the data.

***Visual representation and descriptive statistics*:** The visual representation of the time series under consideration in this analysis is presented in Figure 1. Figure 1 shows that all the graphs display non-stationary patterns except for RF, which is stationary. However, the stationarity property of our variables cannot be determined solely from visual inspection. Our variables' stationary characteristics became clearer after unit root tests were conducted.

Table 2 displays the descriptive statistics and normality tests for the investigated variables. Because every variable's standard deviation is smaller than the mean, we concluded that the research variables are not volatile. The series under discussion are normally distributed since the probabilities of the Jarque-Bera statistic are more than 5%.

Correlation matrices: Correlation matrices for agriculture production (model A), crop production (model B), livestock production (model C), and fishery production (model D) are shown in Table 3. All four correlation matrices show a positive relationship between regressands and regressors.

Table 1. Variables' description and data sources.

Variables	Description	Source
Dependent variables		
AGDP (model A)	Agricultural GDP (constant 2015 US$)	WDI
CGDP (model B)	Crop GDP (constant 2015 US$)	AC
LGDP (model C)	Livestock GDP (constant 2015 US$)	AC
FGDP (model D)	Fishery and Forestry GDP (constant 2015 US$)	AC
Independent variables		
TEMP	Annual temperature (average in ^{0}C)	CCKP
RF	Annual rainfall (average in mm)	CCKP
CO_2	Annual carbon dioxide emissions (kt)	WDI
DC	Domestic credit (constant 2015 US$)	WDI
GCF	Gross Capital Formation (constant 2015 US$)	WDI

Note: AC: Author's Calculations; CCKP: Climate Change Knowledge Portal of the World Bank; WDI: World Development Indicators.

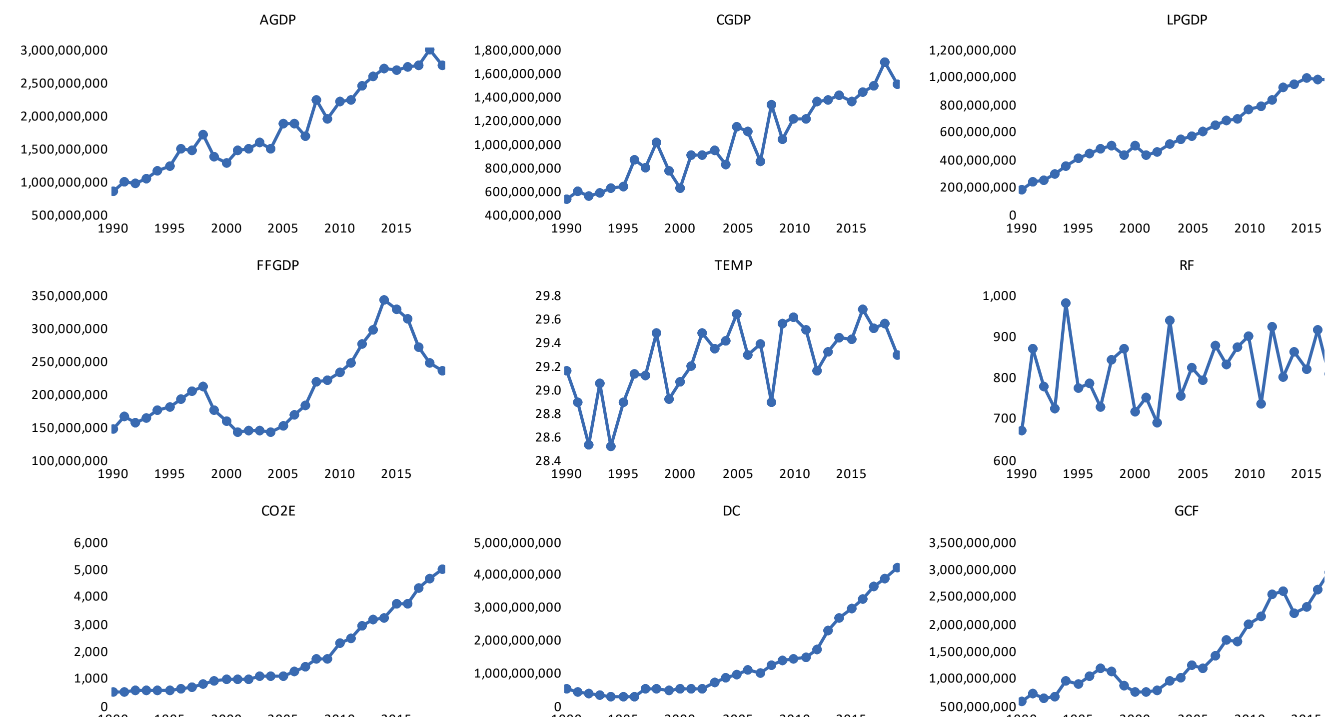

Figure 1. Trend of the study variables in their raw form.

***Unit root tests*:** In this research, we verified the stationary nature of the underlying variables with unit root tests, specifically the Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979) and Phillips-Perron (PP) (Phillips and Perron, 1988) tests. All three cases, with constant, with constant and trend, and without both terms, were evaluated using the level and first difference unit root tests. Both the ADF and PP tests have been analyzed at the 1%, 5%, and 10% significant levels of the Schwarz (SC) criterion. The SC criterion was used to automatically determine the best lag within the software due to the limited size of the sample. The variables have a mixed order of integration [I (0) and I (1)], as shown by the estimated empirical findings for ADF and PP unit root tests in Table 4. No integration of variables occurred at an order larger than two [I (2)], as shown in the results. This supports investigating the relationships between the variables using the ARDL limits testing approach described by Pesaran and Shin (1998) and Pesaran *et al.* (2001).

Table 2. Descriptive statistics of the study variables in their raw form.

Variables	Observation	Mean	Std. Dev.	Jarque-Bera	Probability
AGDP	30	1.84E+09	6.38E+08	2.128868	0.344923
CGDP	30	1.02E+09	3.37E+08	1.850242	0.396483
LGDP	30	6.14E+08	2.59E+08	1.789434	0.408723
FGDP	30	2.07E+08	59316559	3.431116	0.179863
TEMP	30	29.245	0.303812	2.861232	0.239162
RF	30	821.8947	80.66001	1.131719	0.567872
CO_2	30	1786.333	1388.933	4.865885	0.087778
DC	30	1.33E+09	1.19E+09	6.710037	0.034909
GCF	30	1.52E+09	8.34E+08	3.371463	0.185309

Table 3. Correlation analysis of the study variables.

Variables	AGDP	TEMP	RF	$\ln CO_2$	lnDC	lnGCF
Model A: Agricultural production						
AGDP	1					
TEMP	0.625***	1				
RF	0.434**	0.063	1			
$\ln CO_2$	0.973***	0.619***	0.407**	1		
lnDC	0.945***	0.653***	0.365**	0.972***	1	
lnGCF	0.967***	0.554***	0.496***	0.947***	0.913***	1
Model B: Crop production						
CGDP	1					
TEMP	0.632***	1				
RF	0.432**	0.063	1			
$\ln CO_2$	0.944***	0.619***	0.407**	1		
lnDC	0.923***	0.653***	0.365**	0.972***	1	
lnGCF	0.937	0.554	0.496	0.947	0.913	1
Model C: Livestock production						
LGDP	1					
TEMP	0.624***	1				
RF	0.423**	0.063	1			
$\ln CO_2$	0.983***	0.619***	0.407**	1		
lnDC	0.949***	0.653***	0.365**	0.972***	1	
lnGCF	0.967***	0.554***	0.496***	0.947***	0.913***	1
Model D: Fishery production						
lnFGDP	1					
TEMP	0.380**	1				
RF	0.381**	0.063	1			
$\ln CO_2$	0.796***	0.619***	0.407**	1		
lnDC	0.759***	0.653***	0.365**	0.972***	1	
lnGCF	0.865***	0.554***	0.496***	0.947***	0.913***	1

***, **, and * show 1%, 5%, and 10% significance levels, respectively.

Table 4. Results of ADF and PP unit root tests.

	ADF			PP		
Variables	**Constant**	**Constant & trend**	**None**	**Constant**	**Constant & trend**	**None**
At level						
AGDP	-0.212	-3.642**	2.794	-0.737	-3.771**	2.372
CGDP	-0.032	-6.432***	2.728	-1.129	-6.446***	1.994
LGDP	-0.563	-1.987	3.436	-0.553	-2.132	3.304
lnFGDP	-1.364	-2.685	0.253	-1.416	-1.693	0.669
TEMP	-3.032**	-4.872***	0.378	-2.916*	-4.871***	0.333
RF	-6.834***	-8.073***	0.866	-6.747***	-8.276***	0.942
$lnCO_2$	1.164	-2.250	6.311	1.158	-2.262	6.170
lnDC	2.354	-1.378	2.313	0.656	-10.653***	2.119
lnGCF	-0.448	-2.069	2.428	-0.480	-2.002	2.366
At first difference						
dAGDP	-9.103***	-8.929***	-7.439***	-9.618***	-9.446***	-7.123***
dCGDP	-6.860***	-6.746***	-9.198***	-27.021***	-35.419***	-9.861***
dLGDP	-6.611***	-6.479***	-1.224	-6.482***	-6.370***	-4.445***
dlnFGDP	-3.246**	-3.180	-3.317***	-3.246**	-3.180	-3.317***
dTEMP	-8.487***	-4.029**	-8.613***	-19.941***	-19.556***	-13.777***
dRF	-6.124***	-6.348***	-6.103***	-27.541***	-31.293***	-24.707***
$dlnCO_2$	-5.643***	-5.991***	-1.011	-5.628***	-5.943***	-2.827***
dlnDC	-3.730***	-4.363**	-2.035**	-4.602***	-4.792***	-3.725***
dlnGCF	-4.938***	-4.892***	-4.380***	-4.945***	-4.900***	-4.403***

***, **, and * denote the rejection of the null hypothesis by the presence of a unit root at 1%, 5%, and 10% levels, respectively. Automatic lag selection based on SC.

Cointegration test: Each model's long-term relationship between variables was evaluated using the ARDL limits approach for cointegration. Results from all four models and their corresponding critical values are shown in Table 5.

Table 5. Summary of ARDL bounds testing.

Dependent variable	Model	F-statistic	Result
AGDP	A	7.14177	Cointegration
CGDP	B	2.439617	No cointegration
LGDP	C	3.655323	Inconclusive
lnFGDP	D	36.25214	Cointegration
	Significance	Lower bounds I (0)	Upper bounds I (1)
	10%	2.26	3.35
	5%	2.62	3.79
	2.50%	2.96	4.18
	1%	3.41	4.68

These findings indicate that the estimated F-statistic values are larger than the upper limits in models A and D. The conclusion that follows from this is that the null hypothesis must be rejected. Therefore, we inferred that our variables in models A and D are in a state of equilibrium with one another. The derived F-statistic of 2.439 for model B, on the other hand, is less than the lower bounds limits at the 5% level of significance. As a result, we determined that the variables under study were not cointegrated. We cannot estimate the ARDL-ECM (error correction model) in this case. Instead, we estimated the simple ARDL at the first difference. Model C's computed F-statistic of 3.6553 is between the lower and upper bounds limits at a 5% significance level. These results are inconclusive, and we cannot conclude whether or not the variables under investigation are cointegrated. In this case, we will run the ARDL-ECM test and look at the significance and sign of the ECM term. If the ECM term is significant and negative, we will conclude that the variables are cointegrated. Otherwise, we will deduce that they are not cointegrated.

Lag selection: Using the VAR lag length selection test, we identified five distinct criteria (Table 6). These included the Akaike information criterion (AIC), Schwarz information criterion (SC), and Hanna-Quinn information criterion (HQ), as well as the LR (sequence modified LR test statistic). Table 6's results and the SC criterion tell us that lag order one is optimal for models A and C, whereas lag order three is optimal for models B and D.

***Short- and long-term estimations*:**The estimates of temperature, rainfall, CO_2, domestic credit, and gross capital formation effects on agriculture, crop, livestock, and fishery production in Burkina Faso are reported in Tables 7, 8, 9, and 10, respectively.

For model A (Table 7), only CO_2 and GCF benefit agriculture in Burkina Faso in the long term. Temperature and domestic credit also have a positive but insignificant effect on agriculture. Rainfall is found to have a long-term negative but insignificant impact on it. In the short run, rainfall negatively

Table 6. Optimal lag orders results.

Lag	LogL	LR	FPE	AIC	SC	HQ
Included observations: 27						
Model A						
0	-694.506	NA	1.38E+15	51.889	52.177	51.975
1	-590.397	54.236*	9.57E+12*	46.844	48.859*	47.443
2	-550.816	41.046	1.15E+13	46.579	50.322	47.692
3	-493.489	33.972	1.09E+13	44.999*	50.470	6.626*
Model B						
0	-691.368	NA	1.10E+15	51.657	51.945	51.742
1	-584.292	158.631*	6.09E+12	46.392	48.408	46.991
2	-537.251	48.783	4.21E+12	45.574	49.3177	46.687
3	-465.41	42.573	1.37E+12*	42.919*	8.390*	44.546*
Model C						
0	-659.041	NA	9.99E+13	49.262	49.550	49.348
1	-556.971	151.214*	0.05E+11*	44.368	46.384*	44.968*
2	-524.997	33.158	1.70E+12	44.666	48.409	45.779
3	-476.692	28.625	3.15E+12	43.755*	49.226	45.382
Model D						
0	-139.018	NA	1.86E-03	10.742	11.030	10.828
1	-22.216	173.040	5.04E-06	4.757	6.772	5.356
2	8.639	31.997	1.16E-05	5.138	8.881	6.251
3	101.197	54.850*	8.08E-07*	0.948*	.420*	2.575*

* Indicates the lag order selected by the criterion.

Table 7. Results of long- and short-run estimates for model A.

Variables	Coefficient	Std. Error	t-Statistic	Probability
Dependent Variable: AGDP; Selected model: ARDL (1, 0, 1, 0, 0, 1)				
Long-run estimates				
TEMP	61298834	86090112	0.712031	0.4847
RF	-1024028	605522	-1.69115	0.1063
$lnCO_2$	3.07E+08	1.42E+08	2.158286	0.0432
lnDC	77452165	1.03E+08	0.752017	0.4608
lnGCF	6.55E+08	1.33E+08	4.944083	0.0001
Short-run estimates				
C	-2.01E+10	2.74E+09	0	0
D (RF)	-376084	186074.3	-2.02115	0.0569
D (lnGCF)	3.32E+08	1.68E+08	0	0
ECM (-1)	-1.202488	0.164304	-7.31869	0
Goodness of fit				
R^2	0.975554			
Adjusted R^2	0.965776			
F-statistic	99.76618			
Probability	0			
DW statistic	1.928857			

and significantly impacts agriculture, whereas gross capital formation benefits it.

According to the results in Table 8, only domestic credit is found to have a short-run positive impact on crop production in Burkina Faso. However, CO_2 and gross capital formation negatively affect it.

The results of the ARDL-ECM in Table 9 show that the ECM term is significant and negative. This confirms the fact that the variables under consideration are cointegrated. Only CO_2 and gross capital formation positively and significantly impacted livestock in Burkina Faso in the long term.

Table 8. Results of short-run estimates for model B.

Dependent Variable: D (CGDP); Selected model: ARDL (2, 3, 3, 2, 3, 3)				
Variables	**Coefficient**	**Std. Error**	**t-Statistic**	**Probability**
Short-run estimates				
D (CGDP (-1))	-2.377491	0.409488	-5.80601	0.0044
D (CGDP (-2))	-1.01751	0.267058	-3.81007	0.0189
D (TEMP)	1.03E+08	1.04E+08	0.981357	0.382
D (TEMP (-1))	2.92E+08	1.24E+08	2.362211	0.0775
D (TEMP (-2))	-82949299	92685270	-0.89496	0.4214
D (TEMP (-3))				
D (RF)	501838.4	379404	1.322702	0.2565
D (RF (-1))	-1649429	360134.3	-4.58004	0.0102
D (RF (-2))	-2541854	610040.6	-4.1667	0.0141
D (RF (-3))	594630.6	463573.5	1.282711	0.2689
D ($\ln CO_2$)	-1.64E+09	6.40E+08	-2.55769	0.0628
D ($\ln CO_2$ (-1))	1.26E+09	5.84E+08	2.161586	0.0967
D ($\ln CO_2$ (-2))	-6.41E+08	3.06E+08	-2.09389	0.1044
D (lnDC)	5.11E+08	1.43E+08	3.584073	0.0231
D (lnDC (-1))	-4.80E+08	1.49E+08	-3.23104	0.0319
D (lnDC (-2))	1.30E+08	1.14E+08	1.139594	0.3181
D (lnDC (-3))	3.74E+08	1.66E+08	2.249238	0.0877
D (lnGCF)	-5.40E+08	2.20E+08	-2.4553	0.07
D (lnGCF (-1))	8.19E+08	1.87E+08	4.37925	0.0119
D (lnGCF (-2))	1.96E+09	5.39E+08	3.631558	0.0221
D (lnGCF (-3))	-1.02E+09	3.37E+08	-3.04322	0.0383
C	1.41E+08	42381522	3.325226	0.0292
Goodness of fit				
R^2	0.98039			
Adjusted R^2	0.877435			
F-statistic	9.522554			
Probability	0.020508			
DW statistic	1.142417			

Table 9. Results of long- and short-run estimates for model C .

Dependent Variable: LGDP; Selected model: ARDL (1, 1, 0, 0, 0, 0)				
Variables	**Coefficient**	**Std. Error**	**t-Statistic**	**Probability**
Long-run estimates				
TEMP	-30185022	60304831	-0.50054	0.6219
RF	-52841.47	155708.3	-0.33936	0.7377
$\ln CO_2$	1.73E+08	77162639	2.239367	0.0361
lnDC	25562158	57040829	0.448138	0.6586
lnGCF	2.06E+08	66094952	3.116664	0.0052
Short-run estimates				
C	-2.59E+09	5.02E+08	0	0
D (TEMP)	26652055	16388209	0	0
ECM (-1)	-0.570169	0.109418	-5.21093	0
Goodness of fit				
R^2	0.989426			
Adjusted R^2	0.985902			
F-statistic	280.7265			
Probability	0			
DW statistic	2.145845			

Temperature has been found to affect livestock positively in the short term.

Rainfall negatively affects the fishery subsector in Burkina Faso in the long term (Table 10). In contrast, gross capital

formation is found to have a beneficial impact. In the short run, all the variables except gross capital formation negatively and significantly affect fishery production in Burkina Faso. Gross capital formation, on the other hand, favors it.

***Diagnostic and stability tests*:** The estimated models have been subjected to a series of diagnostic and stability tests to gauge their reliability as predictive tools. Statistics from the Ramsey RESET test for error specification, Jarque-Bera test for normality, Breusch-Godfrey LM test for serial correlation, and Breusch-Pagan Godfrey test for heteroscedasticity have their probability above 5% in all models (Table 11). This confirms that our models are free of serial correlation, heteroscedasticity, and error specification problems, and that the residuals follow a normal distribution. Additionally, we used the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMQ) tests to verify the soundness of our models' underlying constructions. The visual representations of the results for both tests for each model in Figures 3, 4, 5, and 6. The CUSUM and CUSUMQ for models A, B, and D fall within the 5% bounds, indicating these models are all stable. In the case of model C (Figure 5), the graph of the CUSUM falls inside the 5% critical limits. However, the CUSUMQ plot is also within the 5% bounds most of the time. However, it must fall within bounds at a 10% significance level. Considering this, we deduced that our models have no diagnostic issues.

Table 10. Results of long- and short-run estimates for model D.

Dependent Variable: lnFGDP; Selected model: ARDL (3, 3, 3, 3, 3, 3)				
Variables	**Coefficient**	**Std. Error**	**t-Statistic**	**Probability**
Long-run estimates				
TEMP	-0.16532	0.092833	-1.78084	0.173
RF	-0.002756	0.000306	-8.99606	0.0029
$lnCO_2$	-0.15561	0.07741	-2.01022	0.138
lnDC	-0.086279	0.041045	-2.10204	0.1263
lnGCF	1.151915	0.089627	12.85238	0.001
Short-run estimates				
C	5.665451	0.234479	24.1619	0.0002
D (lnFGDP (-1))	0.601213	0.038704	15.53351	0.0006
D (lnFGDP (-2))	0.928789	0.045619	20.35972	0.0003
D (TEMP)	-0.082085	0.013504	-6.07859	0.0089
D (TEMP (-1))	0.141393	0.01639	8.626553	0.0033
D (TEMP (-2))	0.073489	0.013443	5.466691	0.012
D (RF)	-0.000782	4.15E-05	-18.8378	0.0003
D (RF (-1))	0.001304	9.12E-05	14.29625	0.0007
D (RF (-2))	0.000728	5.90E-05	12.35101	0.0011
D ($lnCO_2$)	-0.364962	0.05763	-6.33286	0.008
D ($lnCO_2$ (-1))	-0.691693	0.050033	-13.8248	0.0008
D ($lnCO_2$ (-2))	-0.067683	0.045049	-1.50244	0.23
D (lnDC)	-0.193639	0.01919	-10.0908	0.0021
D (lnDC (-1))	-0.086748	0.018693	-4.64076	0.0189
D (lnDC (-2))	-0.216234	0.021281	-10.1611	0.002
D (lnGCF)	0.352712	0.024873	14.1805	0.0008
D (lnGCF (-1))	-0.598394	0.042282	-14.1525	0.0008
D (lnGCF (-2))	-0.61757	0.039803	-15.5155	0.0006
ECM (-1)	-1.118996	0.046462	-24.0839	0.0002
Goodness of fit				
R^2	0.999425			
Adjusted R^2	0.995019			
F-statistic	226.8342			
Probability	0.000416			
DW statistic	2.369611			

Table 11. Diagnostic tests of the study models.

Type of tests	Statistics	Probability
Model A		
Ramsey RESET test	3.3E-06	0.9986
Breusch-Godfrey LM test	0.39290	0.6807
Jarque-Bera normality test	1.19470	0.5502
Breusch-Pagan Godfrey test	3.93583	0.8629
CUSUM	Stable	
CUSUMQ	Stable	
Model B		
Ramsey RESET test	2.7E-01	0.6392
Breusch-Godfrey LM test	0.77987	0.5618
Jarque-Bera normality test	1.83370	0.3990
Breusch-Pagan Godfrey test	17.2076	0.6984
CUSUM	Stable	
CUSUMQ	Stable	
Model C		
Ramsey RESET test	0.33406	0.5697
Breusch-Godfrey LM test	0.31482	0.7337
Jarque-Bera normality test	0.73470	0.6925
Breusch-Pagan Godfrey test	13.5817	0.0591
CUSUM	Stable	
CUSUMQ	Stable	
Model D		
Ramsey RESET test	0.23329	0.6768
Breusch-Godfrey LM test	4.85815	0.3055
Jarque-Bera normality test	0.76450	0.6823
Breusch-Pagan Godfrey test	25.2504	0.3375
CUSUM	Stable	
CUSUMQ	Stable	

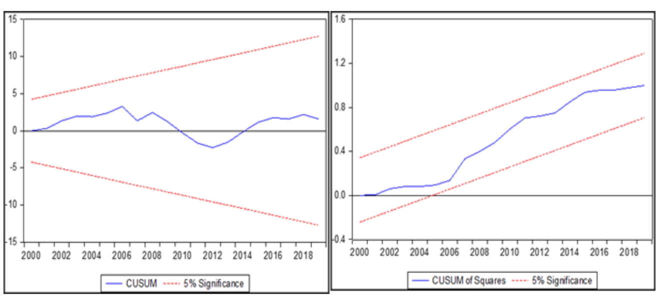

Figure 2. Plot of CUSUM and CUSUMQ for model A.

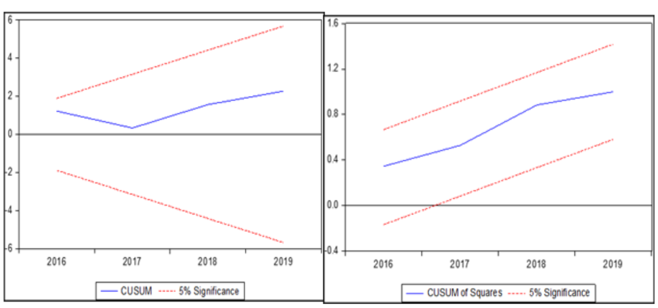

Figure 3. Plot of CUSUM and CUSUMQ for model B.

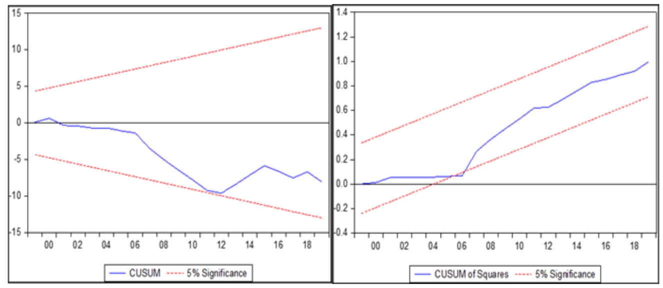

Figure 4. Plot of CUSUM and CUSUMQ for model C.

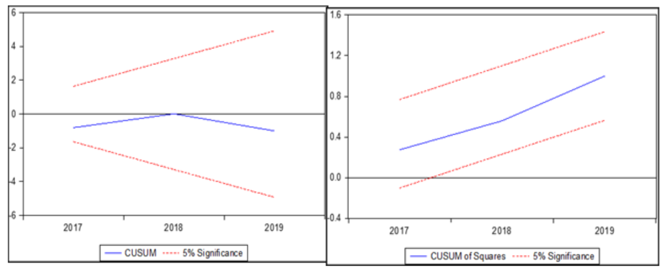

Figure 5. Plot of CUSUM and CUSUMQ for model D.

DISCUSSION

From the analysis, we conclude that the temperature does not impact agriculture and its subsectors in Burkina Faso, except for livestock production (positive effect) and fish production (negative effect) in the short run. Begum *et al.* (2022) found a similar detrimental relationship between temperature and fish production in the short term in Bangladesh, even though it was not statistically significant. The outcome of the beneficial effect of temperature on livestock contradicts Warsame *et al.* (2022), who concluded that temperature adversely affected livestock production in both runs. The result on the insignificant effect of temperature on agriculture and its subsectors is confirmed by research conducted by Janjua *et al.* (2014), Abbas *et al.* (2020), and Pickson *et al.* (2022). This can be explained by the fact that in Burkina Faso, the temperature increased mildly from 29.15^{0}C in 1990 to 29.29^{0}C in 2019 with some punctuations across the years of study (Figure 1).

Our findings reveal that rainfall did not impact agriculture, crop, or livestock production. However, its effect is negative on fishery production in both runs and on aggregate agriculture in the short term. These findings concur with those of Janjua *et al.* (2014), Gul *et al.* (2022a), and Pickson *et al.* (2022), who discovered an insignificant effect of precipitation on agriculture and crop production in Pakistan and China. The study further showed that rainfall has a detrimental effect on the fishery subsector in both runs. In contrast, Begum *et al.* (2022) discovered that rainfall favors fish production in both runs in Bangladesh.

CO_2 has a beneficial effect on agriculture and livestock production in the long term. However, its effect is detrimental

to crop and fishery production in the short term. The findings on agriculture and crop production are partially consistent with Rehman *et al.* (2020) and Pickson *et al.* (2020), who discovered that agricultural productivity is positively impacted by CO_2 in both runs, while crop productivity is negatively affected by it. Our finding on livestock contradicts Warsame *et al.* (2022), who concluded that CO_2 has a short-run beneficial effect on livestock production. The conclusion on fishery productivity is confirmed by Begum *et al.* (2022), who indicated that CO_2 had a short-term detrimental effect on the fishery subsector.

According to our findings, in both runs, domestic credit had no impact on agriculture or livestock production in Burkina Faso. These outcomes are similar to those found by Ntiamoah *et al.* (2022), who reported that domestic credit did not affect soybean production. However, this research pointed out that domestic credit had a boosting effect on crop production in both runs. Another group of researchers, Chandio *et al.* (2021a) and Chandio *et al.* (2022a, b), also discovered that domestic credit increases crop productivity. Our findings also indicated that the fishery subsector is negatively affected by domestic credit in the short run in Burkina Faso.

Gross capital formation is found to have a beneficial effect on agriculture and fishery production in both runs in Burkina Faso. The study further pointed out that gross capital formation also had a favorable long-run impact on livestock production. Our conclusions concur with those of Chandio *et al.* (2022a), who found that gross capital formation positively affected agriculture output in the long term. However, its short-run influence on crop production is negative.

Conclusion: Applying the ARDL bounds testing approach, this article examines the short- and long-run effects of temperature, rainfall, CO_2, domestic credit, and gross capital formation on agriculture production and its subsectors from 1990 to 2019 in Burkina Faso.

Considering agriculture at the aggregate level, the findings have shown an insignificant effect of temperature and rainfall but a positive impact of carbon dioxide (CO_2) in the long term. In the short term, only rainfall has a detrimental effect on agriculture in Burkina Faso. For crop production, only CO_2 is found to have a short-run negative effect. Regarding livestock, temperature has a short-term positive impact, whereas CO_2 has a long-term positive effect. The long-run time series analysis of fishery production has indicated a detrimental impact of rainfall. In the short term, temperature, rainfall, and CO_2 have a detrimental effect on fishery production in Burkina Faso. However, CO_2 has been found to have a short-term negative impact.

The temperature favors livestock production in the short term, but CO_2 has a detrimental short-term impact on it. Temperature, rainfall, and CO_2 have a negative short-run effect on fishery production in Burkina Faso. Rainfall has a short-run detrimental impact on agriculture, whereas CO_2 has a short-run negative effect on crop production. Therefore, the government should:

1. Promote and facilitate the production of livestock in the country.
2. Promote and facilitate the adoption of irrigation systems.
3. Improve Climate System Information (CSI) and make it available for farmers.

***Author contribution*:** L.I.KE-T.D. worked on the concept and design of the study, introduction, literature review, data collection, analysis, and combination of the manuscript. M.K.B. performed the concept and design of the study, methodology, analysis, supervision of the work, and review of the manuscript. S.H. contributed to the manuscript by writing the methodology and helping with the analysis. K.M. contributed to the manuscript by helping with the analysis and improvement of the manuscript.

***Competing interests*:** The authors declare no competing interests.

Funding: This research did not receive any specific grants from funding agencies in the public, commercial, or not-for-profit sectors.

***Data availability*:** The datasets used and analyzed during the current study are available from the corresponding author upon reasonable request.

***Code availability*:** Not applicable.

***Consent to participate*:** All authors participated in this research study.

***Consent for publication*:** All authors submitted consent to publish this research.
article in JGIAS.

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